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Systematic Review and Thematic Synthesis of the Relationship Between Artificial Intelligence and Financial Performance

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Abstract

This study provides a systematic synthesis of the empirical literature examining the relationship between artificial intelligence (AI) adoption and firm-level financial performance. Using a systematic literature review (SLR) methodology, the study analyzes 67 peer-reviewed articles published between 2000 and 2025 that meet predefined inclusion criteria. The selection process followed the PRISMA protocol, and the findings were synthesized through thematic analysis. Overall, the reviewed literature indicates a predominantly positive association between AI adoption and financial performance. In particular, AI investments tend to generate more pronounced benefits in the medium to long term, especially in accounting-based performance indicators such as return on assets (ROA), return on equity (ROE), and operating profit margins. Market-based performance measures also frequently respond positively to AI initiatives; however, these effects appear to be more contingent on contextual and firm-specific conditions. Nevertheless, several studies report limited or even negative short-term outcomes, largely due to high implementation costs, organizational alignment challenges, and learning-curve effects associated with AI deployment. By integrating the empirical evidence through the lenses of the Resource-Based View, Dynamic Capabilities Theory, and Information Processing Theory, this study highlights the conditional nature of financial value creation from AI adoption and provides implications for managers and policymakers.

Keywords: Artificial Intelligence, Financial Performance, Systematic Literature Review, Accounting-Based Performance

JEL Code: C45, G30, C88

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1. Introduction

AI is shaking things up for businesses. It's not just about making things faster or easier—AI is actually changing the way companies make decisions and compete. Machines can now learn to handle all sorts of tasks, and thanks to Natural Language Processing, communication gets clearer and more natural. Predictive analytics? That gives companies more accurate forecasts than ever, which really changes how they perform in their industries. Managers aren't just relying on gut instinct anymore. With AI, they can dig through way more data, do it faster, and be more precise in their analysis (Brynjolfsson & McElheran, 2016, pp. 6). When companies use AI to sift through huge data sets, they cut down on human error and bias. That leads to more stable, efficient decisions, all built on solid predictions. So, for a lot of organizations, AI isn't just another tech upgrade—it's turning into a core part of their strategy. Chen and colleagues (2013, pp. 2-4) point out that, from an economic perspective, AI is driving real improvements in things like return on assets and return on equity. You see it in the numbers. But let's be real: the story isn't the same for everyone. Even though there's plenty of evidence that AI can boost performance, results aren't always consistent across the board. Some studies show big gains, while others don't, which raises questions about what really makes AI pay off. Not every company sees immediate returns from their AI investments. Some reap the benefits right away, others have to wait, and a few might not see much at all—at least not yet.

How much AI actually boosts a company's profits really depends on a lot of things—what they invest in, how they put AI to work, even the company's own culture and environment. There's no magic formula that works for everyone. Some research says AI can seriously help, especially in companies swimming in data. It lets them process information faster and cuts down on decision-making bias (Ransbotham et al., 2018, pp. 4). But there's another side to the story. Other studies point out that AI isn't cheap to set up. High costs, resistance to change inside companies, and not having the right skills on hand can all get in the way or even cancel out any short- or medium-term gains (Agrawal et al., 2019, pp. 45-47). So, there's no simple answer here. The evidence doesn't agree, and that's partly because timing matters—a lot. The pain of big upfront costs and the learning curve really hit in the beginning. But if a company sticks with it and manages to get everyone on the same page, the real benefits of AI usually show up down the line. What's also clear is that studies on this topic aren't all looking at the same things. They use different methods, focus on different industries, and even measure financial success in their own ways. Some dive into tech or manufacturing, others look at banking or services. It's all over the map, which makes it tough to piece everything together into one clear picture (Bughin et al., 2017, pp. 10). A comprehensive evaluation of converging and diverging findings from many industries, performance metrics, and research methodologies will allow for a more sound interpretation of how AI influences an organization's financial performance. In response to this gap, this research will carry out an SLR exploring empirical studies relating to the impact of adopting AI on an organization's financial performance. This SLR aims to create a structured and transparent summary of the effect that AI has on financial performance through identifying key theoretical frameworks used in related literature, categorizing financial performance measures used to evaluate the impact of AI on organizational financial performance, and synthesizing empirical findings from the studies using phenomenology.

This study brings something new to what we already know about how AI affects financial performance. First, it pulls together all those scattered research findings and makes sense of them, laying out a clear framework. Then, it points out the key factors that shape the link between AI and performance—things like which industry we're talking about, how big the company is, and how much data they use. Finally, it lays out some ideas for future research, giving a roadmap for digging deeper into the financial impact of AI with a more focused and thoughtful approach.

2. Theoretical Background

Researchers have looked at how AI affects a company's financial performance from several angles, drawing on different theories that highlight just how broad and interconnected this topic really is (Barney, 1991, pp. 105; Teece et al., 1997, pp. 516; Galbraith, 1973, pp. 5). Instead of sticking to just one way of thinking, most studies mix and match theories to figure out how companies pick up new tech skills—and, more importantly, how they turn that know-how into actual profits (Brynjolfsson & McElheran, 2016, pp. 9; Ransbotham et al., 2018, pp. 6).

You see this especially in how researchers use strategic management theory, information systems, and organizational theory to dig into the link between AI capabilities and company performance (Wamba et al., 2017, pp. 365; Chen et al., 2013, pp. 2–4). Strategic management treats AI as a valuable resource—a way for companies to set themselves apart. Information systems researchers, on the other hand, look at how AI helps companies process information and make decisions faster or better (Ransbotham et al., 2018, pp. 7). Then there's organizational theory, which really zeroes in on how AI interacts with company structures, daily routines, and learning (Galbraith, 1973, pp. 5).

The most common theories here are the Resource-Based View (RBV), Dynamic Capabilities (DC), and Information Processing Theory (IPT), all used to explain how AI ties in with financial results (Barney, 1991, pp.105, 1997, pp. 516; Galbraith, 1973, pp. 5).

Taken together, these approaches make it clear: AI's impact on financial performance isn't straightforward or the same for everyone. It really depends on the company's unique situation, what other resources they have, and the conditions they're working in (Brynjolfsson & McElheran, 2016, pp. 9; Wamba et al., 2017, pp. 365).

Resource-Based View and Artificial Intelligence

The Resource-Based View (RBV) says that companies succeed when they have resources that are valuable, rare, hard to copy, and can't be easily replaced (Barney, 1991, pp. 105). In this model, AI isn't just another piece of tech infrastructure. Instead, it's a strategic asset that shapes what a company can do—how it learns, analyzes, and makes decisions. AI creates value in both day-to-day operations and big-picture planning, mainly through big data analytics, machine learning, and predictive models. But RBV makes it clear: just having AI doesn't mean you'll see instant or guaranteed financial gains. Real-world examples show that AI pays off when companies weave it into their own processes and back it up with the right know-how and skilled people (Brynjolfsson & McElheran, 2016, pp. 9). So, AI on its own doesn't drive value. It works as a complementary resource—you get real results only when you blend it into the company's existing strengths. Good data, employees who know how to use it, and supportive managers all play a huge role in making AI investments succeed.

On decision-making, Brynjolfsson and McElheran (2016, pp. 9) argue that data-driven systems powered by AI deliver bigger gains when companies have already set themselves up with strong management practices. That's how AI moves from being a general-purpose tool to a firm-specific capability that fits RBV's standards for a lasting competitive edge. But RBV also reminds us that the financial payoff from AI depends on the context. As AI tools become more widely available, just having the tech isn't enough anymore. The edge comes when a company combines AI with its own unique data, proven routines, and institutional knowledge (Kraaijenbrink et al., 2010, pp. 351–352). When all these pieces work together in a way that's hard for others to copy, that's when AI becomes truly strategic. Bottom line: There's no simple, universal link between AI adoption and financial performance. The impact of AI depends a lot on what else the company brings to the table, how deeply it implements AI, and how well everything fits together. That's why studies on AI's financial effects often show mixed results—and why any analysis needs to consider the specific organizational context. This framework helps explain why the evidence on AI and financial performance is all over the map. RBV mainly ties AI's benefits to a company's unique resources, but research shows this relationship shifts over time and in different settings. Environmental uncertainty and change play a big part (Chen et al., 2013, pp. 2–4; Agrawal et al., 2019, pp. 45–47). Because of this, Dynamic Capabilities Theory—which looks at how companies recognize, grab, and reshape resources—adds another layer to our understanding (Teece et al., 1997, pp. 516). The next section digs into AI's financial impact from the dynamic capabilities perspective.

Dynamic Capabilities and AI-Driven Performance

The Dynamic Coevolutionary Model builds on the Resource Based View, but it pushes things further. It doesn't just say that having the right resources gives a firm a lasting edge. Instead, it argues that real, long-term advantage comes from how companies evolve alongside an unpredictable environment. It's about how well they can sense, adapt, and rework their resources as the world around them shifts (Teece et al., 1997, pp. 516). This way of thinking really helps explain why some firms outpace others, especially in markets where technology changes fast, uncertainty is everywhere, and competition gets fierce.

AI fits right into this story as a major driver of dynamic capabilities. With AI, companies pick up on signals in their environment earlier and with better accuracy (Li et al., 2017). AI doesn't just stop there—it helps firms weigh strategic options and choose the best paths using smart analytics and predictive tools. When it comes time to act, AI can help companies reorganize their processes, shifting resources quickly and staying a step ahead. So, the link between AI and a company's financial results goes way beyond just making things more efficient. It's about being flexible and able to react in real time. Research shows that AI-driven analytics help firms spot new market trends faster, make sharper choices about pricing and investment, and keep better control over risks. Thanks to all this, AI can boost both the numbers you see in accounting books and the value the market puts on a firm (pp. 365). But here's the catch: DCT points out that AI's impact on financial results isn't straightforward. It mostly runs through how well a company can learn and stay agile. If companies don't update their decision-making, structures, and culture to match their AI investments, the payoff just won't be there. So, just pouring money into technology isn't enough. You need to change the way the organization works and how leaders manage things if you really want to unlock dynamic capabilities (Teece et al., 1997, pp. 518).

In the end, DCT makes it clear that the relationship between AI and financial performance isn't static—it shifts with time and context. That's why research findings on this topic often seem all over the place. The real takeaway? AI's financial impact depends not just on what resources a company already has, but on how well it keeps evolving and reworking its technologies as the world around it keeps changing.

Information Processing Theory

IPT gives us a different way to look at how artificial intelligence actually affects financial performance. Instead of just focusing on technology itself, IPT zeroes in on how well a company's information-processing needs match up with the systems and tech they use to get things done (Galbraith, 1973, pp. 5). This perspective helps explain why some companies see big gains with AI while others don't, especially when things get unpredictable, complicated, or change fast. As businesses drown in more and more data, the old ways of handling information just can't keep up. That's where AI steps in. It boosts an organization's ability to handle information—not just in terms of sheer volume, but also in the quality of insights it pulls from all that messy, varied data. Thanks to machine learning and other advanced analytics, companies aren't just processing more data—they're getting sharper, more useful answers that actually lead to action. Looking at it this way, AI cuts through uncertainty and helps managers make better calls in areas like demand forecasting, dynamic pricing, and managing financial risks. Studies back this up: organizations using AI-driven analytics make more accurate predictions, which leads to better profits and stronger market performance (Ransbotham et al., 2018, pp. 6–7). So, the connection between AI and better financial results really comes down to how much AI boosts a company's information-processing game.

IPT also reminds us that context matters. Companies dealing with lots of uncertainty or constant change have more to gain from AI because they simply need to process more information, faster. On the flip side, in calmer, more predictable environments, investing in AI doesn't move the needle as much. This matches what we see in real life: the impact of AI on the bottom line really depends on things like the industry, how much things are changing, and how tough the decisions are. So, when you put IPT alongside theories like the Resource-Based View and Dynamic Capabilities Theory, you get a more complete picture. The effects of AI on financial performance aren't the same everywhere. IPT gives us a solid foundation for understanding—and explaining—why AI creates value for some firms but not others, setting the stage for a deeper discussion.

Integrative Perspective

When you look at all the theories behind this study together, one thing stands out: there's no simple, one-size-fits-all answer for how AI affects a company's financial performance. The Resource-Based View says AI can help a company make money, but only if it fits with the company's unique resources and strengths. Dynamic Capabilities Theory goes a step further, focusing on how that potential changes over time and how companies adapt to a shifting environment. Then there's Information Processing Theory, which shows how AI boosts financial results by improving decision-making—especially when things get uncertain or complicated (Barney, 1991, pp. 105; Teece et al., 1997, pp. 516; Galbraith, 1973, pp. 5). Altogether, these perspectives make it pretty clear: you can't explain AI's impact on financial performance just by looking at who owns the technology or by checking for quick efficiency wins. The real financial value depends on things like a company's data, its people, how well it learns as an organization, and how quickly it can adapt when things change. That's probably why research results on this topic are so mixed and sometimes even contradictory (Brynjolfsson & McElheran, 2016, pp.9; Kraaijenbrink et al., 2010, pp.351–352).

When you bring all three theories together, the relationship between AI and financial performance doesn't sit still. It shifts and depends on the context. Sure, AI can help companies make better decisions by giving them more information, but whether those decisions actually turn into financial gains depends on how well companies can reshape their technologies and stay flexible. So, the financial payoff from AI isn't just different from one company to the next—it can also change over time (Wamba et al., 2017, pp. 365; Ransbotham et al., 2018, pp. 6–7). This way of looking at things sets a strong foundation for pulling together what we've learned from the literature review. Up next, I'll break down the studies on AI and financial performance by themes, looking at how they measure performance, what industries they cover, the methods they use, and any important context. Doing this helps pinpoint when AI's financial impact gets stronger or weaker. This approach will also link directly to the theoretical and empirical analysis in the discussion section.

When you look at the research on how AI affects financial performance, you notice a pretty mixed picture. Some studies say AI boosts profits or market value right away, but others find the benefits show up later, come through indirect paths, or really depend on the situation. You can't just lean on one theory to explain all this—there's more going on. It's not just about having the latest tech. What really matters is how companies work AI into their daily routines, where they use it, and how they handle uncertainty out in the real world (Brynjolfsson & McElheran, 2016, pp. 9; Agrawal et al., 2019, pp. 45–47).

When you bring together ideas from the Resource-Based View, Dynamic Capabilities Theory, and Information Processing Theory, you start to see why the story is so layered. Sure, AI gives companies sharper tools for making decisions. But turning those smart decisions into real, lasting financial gains? That depends on whether a company can keep updating how it uses AI and actually learn from working with these tools. So, it doesn't make sense to treat the link between AI and financial performance as a simple "adopt and profit" deal. It's more of an ongoing, evolving process (Teece et al., 1997, pp. 516; Ransbotham et al., 2018, pp. 6–7).

That's why this study takes an integrative approach, using a systematic literature review and thematic synthesis. In the next sections, you'll see how the research breaks down—organized by theory, methods, and context—so it's easier to spot when AI actually lifts financial performance and when the results are less clear. The discussion ties everything back to the bigger theoretical picture, aiming to add something meaningful to the field, both in terms of concepts and on-the-ground evidence.

3. Methodology

This study uses a Systematic Literature Review (SLR) to dig into what researchers have actually found about how artificial intelligence (AI) connects to financial performance. There's a ton of new work out there, but it's all over the place—different fields, industries, methods. That makes it tough to line up the results or draw big-picture conclusions. That's where the SLR comes in. It helps make sense of this scattered research by following a clear, step-by-step process.

Unlike regular narrative reviews, SLRs set out their research protocols from the start. They spell out exactly how studies get picked and how data gets analyzed, so you can see what's happening at every stage and even repeat the process if you want. In areas as messy and complex as AI and finance, this kind of structure cuts down on bias and keeps the analysis sharp and consistent (Tranfield et al., 2003, pp. 215). That's why SLR is a solid choice for studying the financial impact of fast-moving technologies like AI.

In this paper, the SLR isn't just about listing what others have found. It digs deeper, comparing the theories, methods, and situations researchers use to explain how AI affects financial performance. This way, we get a better sense of when AI really boosts financial results—and when it doesn't move the needle much. All of this sets the stage for the themes and discussion in the rest of the study.

Review Protocol and Data Sources

To make sure the SLR is both trustworthy and thorough, we stuck to a review protocol right from the start. This protocol lays out four main steps: picking which databases to use, figuring out the search strategy, setting clear inclusion and exclusion criteria, and then tackling data analysis. By sticking to this structure, we cut down on any personal bias when choosing which studies to include.

We searched for relevant literature in two main databases: Web of Science (WoS) and Scopus. We picked these because they both cover a huge range of respected, peer-reviewed journals in finance, accounting, and information systems. They're also well-known for their citation indexing, which helps boost academic quality and visibility. Boo et al. (2015) even point out that WoS and Scopus are the top data sources for systematic reviews.

To keep things consistent, we focused only on peer-reviewed journal articles. We left out conference proceedings, book chapters, and working papers since they follow different review processes and don't always line up in terms of empirical results. We also limited our search to studies published in English. This way, we could compare studies more directly and keep methodological differences to a minimum across the international literature.

With these choices and the protocol in place, our search process pulled together a solid set of relevant, high-quality studies on artificial intelligence and financial performance. The next sections break down how we searched, what criteria we used to select studies, and how we analyzed them.

Search Strategy and Keywords

To ensure the comprehensiveness and replicability of the systematic literature review, a structured search strategy aligned with the research question was developed. The primary objective of this strategy was to identify empirical studies examining the relationship between artificial intelligence applications and firm-level financial performance in a manner that is as inclusive as possible while remaining analytically selective. Accordingly, the selection of keywords was designed to balance conceptual breadth with empirical focus.

The keywords used in the search process were applied to the title, abstract, and author keywords fields. This approach ensures that studies are identified not merely based on peripheral mentions, but in a way that directly reflects their core research focus. Commonly employed in systematic review studies, this method helps reduce false positives and facilitates the exclusion of irrelevant publications (Paul & Criado, 2020, pp. 3). Based on this approach, the search string was structured as follows:

(“artificial intelligence” OR “machine learning” OR “AI adoption”)
AND
(“financial performance” OR “firm performance” OR “profitability” OR “firm value”)

The first group of keywords was defined to capture artificial intelligence both as a general concept (“artificial intelligence”) and through its application-oriented forms (“machine learning”, “AI adoption”). This choice was intended to include studies that conceptualize AI not only as a technical tool but also as an organizational-level managerial and decision-support capability. As a result, empirical studies examining firms with varying levels of technological maturity and different modes of AI implementation were incorporated into the scope of the review.

The second group of keywords was constructed to reflect the multidimensional nature of financial performance. While the terms “financial performance” and “firm performance” capture general performance measures, the inclusion of “profitability” and “firm value” allows for the identification of studies focusing on more specific indicators, such as accounting-based profitability ratios (e.g., ROA, ROE) and market-based measures (e.g., Tobin’s Q, market value). This approach is consistent with the prevailing view in the literature that financial performance should not be reduced to a single metric.

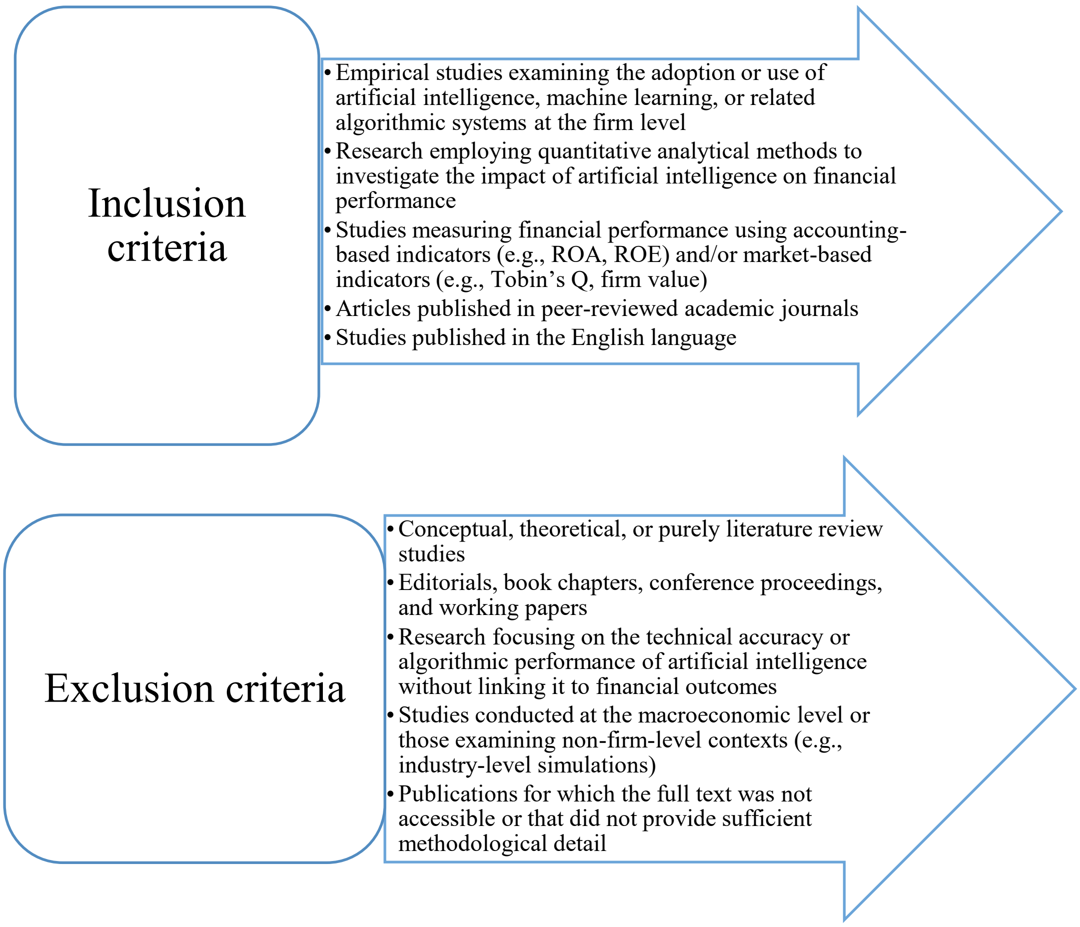
Structuring the search strategy in this manner enabled the systematic identification of studies examining the AI–financial performance relationship across different theoretical frameworks, industries, and national contexts. At the same time, this strategy functioned as an analytical pre-filter for the inclusion and exclusion criteria applied in subsequent stages, thereby strengthening the internal coherence of the review. In this respect, Section 3.2 constitutes the methodological backbone of the study, directly underpinning the subsequent selection and analysis phases.

Inclusion and Exclusion Criteria

The reliability and validity of findings derived from systematic literature reviews largely depend on the clarity and consistency of the inclusion and exclusion criteria applied. Accordingly, the studies identified through the search strategy described in Section 3.2 were evaluated based on predefined and explicit criteria in order to construct a sample that is directly relevant to the research question and methodologically comparable. This approach reduces selection bias and enhances the internal validity of the review (Kitchenham et al., 2009, pp. 15).

In defining the inclusion criteria, primary emphasis was placed on the core objective of the study, namely the empirical examination of the relationship between artificial intelligence adoption and firm-level financial performance. In line with this objective, only studies that met the following conditions were included in the review:

Figure 1. Inclusion and Exclusion Criteria Applied in the Study Selection Process



As illustrated in Figure 1, the inclusion criteria applied in this study enable the evaluation of studies conducted across different country and industry contexts within a common analytical framework, thereby supporting the coherence of the thematic synthesis process. In contrast, studies falling outside the scope of the research question or those that do not allow for empirical comparability were systematically excluded and are specified as exclusion criteria in Figure 1.

The exclusion process was particularly effective in eliminating studies that address the impact of artificial intelligence on financial performance in an indirect or hypothetical manner, thereby enhancing the direct comparability of the analyzed findings. Consequently, the criteria defined in Section 3.3 ensured that the literature review was not only comprehensive but also analytically focused. This structure facilitates the transparent reporting of the screening and selection process (PRISMA) described in the subsequent section and strengthens the replicability of the methodological procedure. In this regard, the following stage provides a detailed account of how studies were screened and how the final sample was derived.

Screening Process and PRISMA Compliance

We followed the PRISMA guidelines for our literature search and screening—mainly because they keep things transparent and easy to replicate (Moher et al., 2009, pp. 265). PRISMA makes it clear exactly how many studies we cut at each step, which helps tighten up the process.

First, we used the search strategy from Section 3.2 and ran searches in both Web of Science and Scopus. This gave us a big pile of papers with keywords tied to artificial intelligence and financial performance. We merged all these records into one list and got rid of any duplicates. Removing duplicates stopped us from counting the same findings more than once, so the sample stayed clean.

Next, we screened the remaining studies by looking at their titles and abstracts, using the criteria from Section 3.3. If a study just mentioned artificial intelligence in passing, didn’t directly connect it to financial performance, or skipped firm-level analysis, we dropped it.

After that, it was time to read the full texts of the studies that made it through. Here, we paid close attention to how the research was designed, which financial performance indicators they used, and how they measured artificial intelligence. We excluded anything that didn’t back up its claims with solid evidence or had shaky methodology. Only the studies that checked all the boxes moved on to the final sample.

We summed up all these steps in a PRISMA flow diagram, which lays out how many studies we started with, how many duplicates we removed, and how many papers made it through each stage. The diagram gives readers a clear, step-by-step look at the whole search and screening process, adding real depth to the methods section.

All in all, sticking to PRISMA boosted the objectivity, reliability, and scientific strength of our review. It set a solid base for the data extraction and thematic analysis in the next section, and it helps draw clear lines around how we interpret our findings.

Data Extraction and Analysis

Here's how the data extraction process went for this study: I organized it to match what's considered best practice in the literature on systematic reviews. I gathered detailed info from each empirical study—who wrote it, when it was published, the industry or context, the type of AI used (like machine learning, deep learning, or automation), what the AI was used for (processes, financial decisions, risk management), which financial performance measures they tracked, and, of course, the results.

For analyzing all this data, I used thematic analysis, taking my cue from Braun and Clarke's framework (2006, pp. 87). Instead of sticking to some rigid set of hypotheses, thematic analysis lets you look for patterns and themes that pop up naturally from the literature. The process went like this: I got familiar with the data, did some initial coding, identified potential themes, checked them for consistency and distinctness, and finally, gave each theme a clear definition and label.

This approach helped me move past the simple question of whether AI affects financial performance or not. What jumped out was that a lot of studies assume certain ways AI influences financial performance, even if they don't spell them out. Thematic analysis helped untangle these ideas, so I could see how the literature really fits together in a more organized way.

After digging through everything, a few key themes stood out. First, AI's impact on things like operational efficiency, cost structure, and resource allocation—these have a direct effect on financial performance. Next, AI's influence on information processing and strategic decision-making came up, which affects financial performance more indirectly. Then, there's the role of mediating resources, and finally, the importance of contextual factors—both of which also shape financial performance, but not in a straightforward way.

What's interesting is how these themes line up with the theories I discussed earlier in Section 2. The Resource-Based View shows that AI's financial value depends on how well it fits with a firm's own capabilities and resources. Dynamic Capabilities Theory points out that it also matters how quickly a firm can respond to changes in its environment. And according to Information Processing Theory, AI's value really comes into play when there's a lot of uncertainty or complexity. The thematic analysis highlights all of this quite clearly.

So, to sum up, the relationship between AI and financial performance isn't simple or universal. It depends on how organizational strengths, supporting resources, and the environment all interact. These findings set the stage for the next section, where I'll lay out the main themes in more detail, and they help explain why AI investments lead to different financial outcomes in different settings.

4. Findings: Thematic Analysis

This section attempts to synthesize the findings of the included studies within the framework of thematic analysis, as presented in the following sections. As has been followed in most of the prior systematic literature reviews, the findings are presented based on the dominant themes emerging from the literature rather than presenting the findings of the included studies separately. This allows for a much more abstract and theoretical approach, which helps in developing an understanding of the underlying mechanisms between artificial intelligence and financial performance, as has been emphasized by Braun and Clarke (2006) on page 87 of their book.

Within this section, the findings are presented based on the themes emerging from the literature. A summary of the thematic presentation of the included studies, along with the methodology and findings on financial performance, is presented in Table 1.

Table 1. Expanded Thematic Classification of Empirical Studies on AI and Financial Performance

Theme	AI Application Domain	Data Type	Empricial Method	Financial Performance Measures	Effect Direction	Representative Studies
Accounting-Based Performance Effects	Process automation, demand forecasting, cost optimization	Firm-level panel data	Panel regression, FE/RE, GMM	ROA, ROE, Operating Margin	Positive (medium–long term)	Brynjolfsson & McElheran (2016, pp. 8–10); Kinkel et al. (2022); Cao et al. (2022, pp. 56–58); Tan et al. (2025), Yang &Yang (2025:pp. 3-14), Kawadkar (2026, pp. 423-426)
Market-Based Performance Effects	Algorithmic decision support, investment analytics, AI announcements	Market data, event windows	Event study, panel regression	Tobin's Q, stock returns, market-to-book ratio	Positive / Mixed	Cockburn et al. (2018, pp. 22–25); Benaich & Hogarth (2019, pp. 41–43); Babina et al. (2020, pp. 18–21); Gupta et al. (2024, pp. 77–80), Lim (2024, pp. 6-46), Alam et al. (2025, pp. 14–18), Morina (2025, pp. 35-39), Oldemeyer et al. (2025, pp.4-21), Fradelos (2026, pp. 3-18).
Sectoral and Contextual Heterogeneity	Manufacturing, finance, e-commerce, healthcare	Multi-industry samples	Sub-sample analysis, interaction models	Mixed indicators	Sector-dependent	Bughin et al. (2017, pp. 9–11); Wamba et al. (2017, s. 365); Daugherty & Wilson (2021, pp. 92–94); Zeng et al. (2023, pp. 301–304), Huang et al. (2019, pp. 55–65), Masod&Zakaria (2024, pp.155-156), Pluskota et al (2026, pp. 2-25)
Moderating Organizational Factors	AI–organizational fit, analytical culture	Survey data + financial data	Interaction regressions, SEM	ROA, Tobin's Q	Conditional	Agrawal et al. (2019, pp. 45–47); Ransbotham et al. (2018, pp. 6–7); Firk et al. (2022, pp.

Theme	AI Application Domain	Data Type	Emprical Method	Financial Performance Measures	Effect Direction	Representative Studies
						118–121); Verhoef et al. (2025, pp. 33–36), Dubey et al. (2020, pp. 4-12); Benzakour et al. (2026, pp.607-616).
Implementation Costs, Risks, and Delayed Effects	Infrastructure investments, cybersecurity risks	Short- and long-term financial data	Difference-in-differences, dynamic panel models	Short-term profitability	Negative / Delayed	Kinkel et al. (2022); Du & Xie (2023, pp. 64–67), Wang &Chen (2025, pp. 3); Brock & von Wangenheim (2019, pp. 110–130), Pantelis (2025, pp. 1-5), Hoque&Irfan, (2025, pp. 26-28)

In this context, it was found that the results were categorized according to thematic criteria, taking into consideration different types of performance measurement, sectoral characteristics, organizational characteristics, and time-related factors. In the following sections, these thematic elements, which were revealed in the literature, will be examined in an orderly manner.

Artificial Intelligence and Accounting-Based Financial Performance

A large body of empirical literature investigates the association between the adoption of artificial intelligence technologies and accounting-based financial performance measures, such as return on assets (ROA), return on equity (ROE), and operating profitability. A notable feature of this literature is the fact that the empirical models employed typically involve performance measures that directly capture the effect of AI adoption on firms' internal processes. Overall, the evidence provided by the literature indicates a positive association between AI adoption and firms' profitability, especially in the medium to long term. In this sense, the efficiency effects of AI technologies in areas such as process automation, forecasting, and decision-making are concretely reflected in accounting-based performance measures (Bağcı & Yerdelen Kaygın, 2020).

Brynjolfsson and McElheran (2016, pp. 8-10) show that organizations that implement data-driven decision-making processes are able to attain higher levels of productivity and profitability compared to organizations that do not utilize these kinds of decision-making processes. Since these kinds of decision-making processes are supported by artificial intelligence algorithms, any improvements in processing information quickly and accurately can lead to more efficient allocation of resources, hence reducing costs of production. Chen et al. (2013, pp. 2-5) also show that organizations that implement artificial intelligence algorithms in process automation are able to attain higher levels of ROA and operating profit margins. These kinds of findings support the Resource-Based View perspective that artificial intelligence can lead to strategic value once embedded in firm-specific processes.

At the same time, the relevant literature also points to the temporal dimension of the impact of AI on accounting-based performance. Indeed, some studies draw attention to the fact that, in the initial stages of the adoption of AI, significant costs are associated with the infrastructure, data integration, and the procurement of skilled human capital. These costs could negatively impact ROA and other accounting-based measures of performance in the short term (Agrawal et al., 2019, pp. 45-47). Therefore, some studies find that the impact of AI on accounting-based performance is neutral to slightly negative in the short term, but positive in the longer term, as the learning curve takes place and economies of scale are realized.

This temporal pattern also explains the mixed findings reported in the literature and highlights the fact that the relationship between artificial intelligence and financial performance is not static in nature, but rather dynamic. From this viewpoint, accounting-based performance indicators are important, yet temporal, indicators of the assessment of the value creation potential of artificial intelligence in firms.

In conclusion, although the pioneering studies in the literature focused on establishing the potential of artificial intelligence in improving accounting-based financial performance, the more recent studies in the literature have enriched the understanding of the temporal, organizational, and sectoral nature of the relationship between artificial intelligence and financial performance. This evolution in the literature explains the mixed findings reported in the literature and highlights the need to use a dynamic analytical approach in conceptualizing the relationship between artificial intelligence and financial performance.

Artificial Intelligence and Market-Based Financial Performance

Unlike accounting-based measures, market-based measures of financial performance, such as Tobin's Q, stock returns, and market-to-book ratios, are based on investors' expectations about future cash flows and growth opportunities of firms. Therefore, the impact of artificial intelligence adoption on market-based financial performance offers valuable insights into the perceived strategic value of artificial intelligence as a means of gaining competitive advantage, as opposed to its impact on current profitability.

Significantly, a substantial body of empirical literature has demonstrated that the capital markets generally react favorably towards announcements and investments in AI. More specifically, studies that have adopted an event study approach have demonstrated that firms experience abnormal stock returns in the short term following public announcements regarding their initiatives in AI. For example, Cockburn et al. (2018) have demonstrated that firms' market valuations increase significantly following their investment in AI-oriented innovation activities, especially in industries that have high technology content (pp. 22-25).

Furthermore, Benaich & Hogarth (2019) have demonstrated that firms that have been perceived as leaders in AI have higher Tobin's Q ratios, which indicates that AI is perceived as an indicator of innovativeness and future preparedness (pp. 41-43). These results reinforce the point that market-based performance is dependent not only on current financial performance but also on firms' orientation towards technology and their vision for the future.

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Recent research has continued to stress that such market responses are conditioned rather than unconditional. In the post-2020 literature, it has been found that the impact of AI investments on market value has been closely dependent on pre-existing digital capabilities, data infrastructure, and quality of corporate governance within the firm. For example, it has been found that AI-related announcements by firms that have high analytical maturity are more credible and hence lead to greater market impact (Ransbotham et al., 2018, pp. 6-7).

On the other hand, some research has found that market responses may be neutral or even negative. For example, where AI investments are not strategically aligned, involve uncertain costs, and are considered risky, market players may take a cautious position. For example, it has been found that capital markets do not necessarily consider AI investments as positively impacting firm value; instead, they look for positive signals regarding organizational fit (Agrawal et al., 2019, pp. 45-47).

Overall, evidence from market-based performance studies suggests that the financial effects of artificial intelligence are largely shaped by expectations, perceptions, and strategic signaling. This pattern is consistent with the lagged effects observed in accounting-based performance indicators and indicates that market mechanisms often price AI primarily as a source of future value creation. Consequently, the relationship between artificial intelligence and market-based financial performance is closely linked not to the technology itself, but to how firms position AI strategically and communicate these investments to investors.

Sectoral and Contextual Heterogeneity

As revealed by the studies considered in the systematic review, the influence of the adoption of artificial intelligence on financial performance differs significantly depending on the industry sector and organizational context. This finding is consistent with theoretical expectations that suggest that the value creation potential of AI is not homogeneous and is instead significantly dependent on the context in which the organization competes.

As revealed by the empirical evidence, the influence of AI investments on financial performance is more significant in data-intensive industries. Organizations in the manufacturing, finance, retail, and digital platform industries are more likely to benefit from the increased efficiency and profitability resulting from the application of AI in forecasting, automation, and risk analytics. According to the findings of Bughin et al. (2017, pp. 9-11), in their extensive research across multiple industries, the application of AI is more likely to result in the improvement of ROA and productivity in the finance and advanced manufacturing industries (Bağcı & Öner, 2025).

For instance, research focusing on the financial sector indicates that the application of AI technologies such as algorithmic credit scoring, fraud detection, and portfolio optimization have a positive influence on both accounting-based and market-based performance indicators. In the same vein, in the retail and logistics industries, the application of AI technologies such as demand forecasting and inventory optimization has a positive influence on the operating profit margins of firms by reducing costs (Wamba et al., 2017, pp. 365). These research findings are consistent with the predictions of the Information Processing Theory, which argues that the economic value generated by AI technologies is higher in information-intensive environments (Öner & Bağcı, 2025).

However, in industries with low data intensity and standardized processes, the financial performance implications of AI technologies are limited and heterogeneous. For instance, in traditional service industries or labor-intensive industries, the time required for the translation of AI investments into performance benefits is relatively longer, and the success of AI implementation is limited due to alignment issues. From a Dynamic Capabilities perspective, these research findings highlight the importance of firms' ability to integrate AI technologies with existing processes.

However, contextual heterogeneity does not stop at sectoral levels; geographical and institutional contextual factors also play important roles in explaining the relationship between AI and financial performance. In countries with robust institutional infrastructures, data governance, and flexible regulations, the financial outcomes of AI investments are more evident. On the contrary, data privacy issues, lack of digital infrastructure, and insufficient human capital may limit the financial outcomes of AI investments in specific contexts.

Recent studies (2023-2025) focuses more on firm-level contextual heterogeneity, which plays a crucial role in explaining the relationship between AI investments and financial outcomes. In addition to sectoral heterogeneity, firm-level contextual heterogeneity, including firm size and levels of digital maturity, plays a crucial role in explaining the financial outcomes of AI investments. Large and multinational corporations may attain higher financial outcomes from AI investments due to economies of scale.

Overall, these results suggest that the relationship between artificial intelligence and financial performance is not homogeneous or universal; instead, it has a multi-layered structure depending on sectoral factors and organizational contexts. This heterogeneity explains the conflicting findings reported in the literature. The financial performance of AI investments needs to be assessed in a context-dependent manner. The diversity of the topics is also evident from the classification of the articles in Table 1. The role of the moderators from the regulatory and organizational contexts is further discussed in the following subsection.

Moderating Factors in the AI–Financial Performance Relationship

The significant percentage of studies reviewed in the systematic review suggests that the relationship between the adoption of artificial intelligence and financial performance is not direct and unidirectional, but rather conditioned by a number of organizational and regulatory factors. Such an approach offers a critical framework for understanding the reasons for the reported heterogeneity and, at times, contradictory nature of the relationship between the financial performance of AI adoption.

At the organizational level, the size of the organization, analytical culture, and the quality of human capital and data maturity have been the most studied moderating factors. Ransbotham et al. (2018, pp.6-7) suggest that organizations that benefit from the adoption of AI to a significant degree not only have access to technologically advanced infrastructures but also have analytical cultures and access to skilled human capital to accompany such technological advancements. Such a conclusion, therefore, supports the Resource-Based View framework, which suggests that AI does not create value in isolation but rather in conjunction with other organizational resources.

Likewise, Agrawal et al. (2019, pp. 45-47) contend that the relationship between AI investments and financial performance is significantly moderated by organizational redesign and changes in the process of decision-making. Their study suggests that when AI investments are implemented without any corresponding changes in the traditional structure of the organization, there is no corresponding improvement in productivity. Instead, there is a negative pressure on performance in the short term. This finding is consistent with Dynamic Capabilities Theory, which emphasizes the importance of the ability of organizations to adapt and redesign their resources in relation to technological investments.

Another factor that is important in moderating the relationship between AI investments and financial performance is the regulatory environment. It is important to note that regulations on data privacy, AI ethics, and algorithmic transparency have a direct relationship with the ability of organizations to scale and commercialize AI investments. Organizations operating in environments with more restrictive data privacy regulations, such as the EU, are likely to be more cautious in deriving financial returns from AI investments. This is likely to result in delayed performance effects. However, in environments with more permissive regulations, AI investments are more likely to be quickly commercialized.

Recent empirical research findings from 2023 to 2025 also support that, in particular, market-based performance measures are subject to a strong impact of regulatory uncertainty. As far as investors' perceptions of legal and ethical risks of AI-related projects are concerned, Tobin’s Q and stock returns are subject to varying impacts depending on firm- and country-level contexts. As with the results of market-based measures discussed in Section 4.2, these results support that, in particular, financial performance implications of AI are subject to influences of expectations as well as perceptions, not just outcomes.

Lastly, examining organizational and regulatory moderators in combination can account for why, in some organizations, investments in AI are associated with robust and sustained financial benefits, whereas in others, investments in AI are associated with limited or lagging results. These results suggest that the impact of AI on financial outcomes is contextual, multidimensional, and dynamic, and as such, any attempts at one-size-fits-all solutions are unlikely to succeed. This framework offers a robust basis for drawing out implications from both the empirical and theoretical results in the Discussion section that follows.

Implementation Costs, Risks, and Delayed Effects

Although a significant amount of the literature proves the positive impact of artificial intelligence adoption, a significant number of studies emphasize the complexity of the impact of artificial intelligence on financial performance, considering the costs, risks, and timing dimensions. It is important to mention that, during the initial phase of the investment, the impact of artificial intelligence on financial performance could be restricted, positive, or even negative.

The investment costs of artificial intelligence projects are generally high. The investment costs include the costs of hardware infrastructure, data integration, software, and skilled manpower. These costs could negatively impact the short-term financial performance of the firms. According to Agrawal et al. (2019), the costs of artificial intelligence projects delay the impact of artificial intelligence investment, and the financial returns of artificial intelligence investment are realized over time rather than being realized at the time of investment (pp. 45-47).

Moreover, the learning process is also significant in the context of the delay in the impact of artificial intelligence investment. Kinkel et al. (2022) have proven that the firms could face productivity losses during the initial phase of artificial intelligence investment; however, the learning curve effects could positively impact the financial performance of the firms. This evidence indicates that the financial effects of AI investments are dynamic and time-dependent.

The risk dimension is also increasingly emphasized in the literature. Cybersecurity risks, algorithmic errors, and ethical issues are just a few examples of factors that can limit the possible financial performance of AI applications. In particular, in industries where there is high regulatory uncertainty, the scaling of AI investments is more conservative, resulting in a weaker impact on accounting- and market-based performance measures.

In this context, a major part of the divergent results reported in the literature can be ascribed to differences in terms of time horizon, measurement approaches, and implementation maturity. Short-term studies focus on cost effects, while long-term studies reveal the value created by AI in terms of economies of scale, learning effects, and organizational transformation.

Overall, the key to understanding the relationship between artificial intelligence and financial performance lies in not only the adoption of artificial intelligence but also the timing of the investment, the level of investment, and the ability of firms to manage risk. These results shed light on the contextual, conditional, and lagged nature of the financial effects of artificial intelligence and serve as a strong analytical background for the Discussion section of the analysis discussed in the next chapter.

5. Discussion

This study aims to investigate the link between the adoption of artificial intelligence and the financial performance of firms through a systematic literature review and thematic analysis. The results of this study reveal the effects of artificial intelligence on the financial performance of firms, which are not universal or linear but rather dependent on the context. The results of this study will be discussed in the light of the relevant theoretical perspectives, along with the contributions of this study to the existing literature.

Theoretical Implications

Firstly, the results pertaining to accounting-based financial performance indicators are broadly consistent with the Resource-Based View (RBV) approach. The reviewed studies imply that the contribution of AI to financial performance is

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achieved when the technology is integrated into firm-specific processes and augmented by supporting resources. This also suggests that the value of AI as a technology is lost when its imitability increases, and the technology becomes a mere resource when combined with firm-specific resources such as data, human capital, and processes (Barney, 1991, pp. 101-102).

In contrast, the results pertaining to market-based performance indicators imply that investors tend to perceive the use of AI in terms of its potential impact on the firm's growth and innovativeness in the future. This explains the quicker market reactions to the use of AI in comparison to accounting-based indicators. However, the conditional nature of these reactions also clearly suggests that the use of AI is not necessarily perceived as a valuable resource by the market.

Reconciling Conflicting Empirical Findings

One of the significant contributions of this study is the identification of the heterogeneity in the relationship between AI and financial performance, which is specific to each sector and context. The results show that the financial returns of AI investments are higher in data-intensive industries, whereas the impact of AI investments is less significant in industries with data infrastructure constraints and organizational transformation capabilities. Consistent with the IPT, the results imply that the potential for creating value through AI investments is positively related to environmental uncertainty and information complexity.

The regulatory environment and corporate governance structures are critical factors that determine the financial performance of AI investments. In countries with strict data protection and AI-related regulations, the financial returns from AI investments are realized in a delayed manner. The results of this study are significant for understanding the reasons for the inconsistent findings of studies using cross-country comparative approaches.

Implications for Accounting and Finance Research

The implications of the findings of the review for accounting and finance research are significant. Firstly, the review's findings emphasize the need to transcend the conventional binary approach to the study of AI adoption and to consider more nuanced measures of AI implementation. Secondly, the review's findings suggest that financial performance is best conceptualized as a multidimensional construct, which includes both accounting and market-based approaches.

Furthermore, the review's findings emphasize the increasing salience of intangibles and digital capabilities in the context of firm performance. The conventional approach to financial reporting may not fully recognize the value of AI-related capabilities, which has important implications for accounting research.

Managerial Implications

From a managerial perspective, the results of this study suggest that managers should not assume that investing in AI automatically guarantees better financial outcomes. Rather, managers should understand that AI is a complementary technology whose impact on financial outcomes depends on various organizational conditions. Investments in human capital, organizational, and data-related infrastructure seem to be essential pre-requisites to leveraging the financial benefits of AI.

6. Conclusion And Future Research Agenda

This study presents a systematic literature review of empirical studies on the association between the adoption of artificial intelligence (AI) and financial performance. The review of 67 peer-reviewed articles aims to offer a structured understanding of the theoretical effects of AI on financial performance through a review of various contexts.

Summary of Key Findings

The review also shows that the majority of the studies find a positive relationship between AI adoption and financial performance, especially with regard to accounting-based measures such as return on assets and operating margins. Market-based measures also respond positively to AI-related initiatives, which reflects the optimism of investors about the future value of AI capabilities. However, the findings are not uniform.

The thematic synthesis shows that the financial impact of AI adoption is contingent upon organizational, industry, and temporal factors. Data-intensive industries and firms with strong analytical cultures and complementary human capital are likely to enjoy the long-term financial benefits of AI adoption. However, studies that find no significant impact of AI adoption also show significant costs of implementation, organizational inertia, and learning lags.

Theoretical Contributions

This review also makes an academic contribution by bringing together disjointed empirical evidence through established theoretical lenses. From an RBV perspective, it is clear that AI represents an important intangible resource for firms, with its associated financial value being contingent upon firm-specific integration and complementarity (Barney, 1991, pp. 105). Moreover, through the lens of Dynamic Capabilities, it is clear that only certain firms can capitalize on the adoption of AI in terms of long-term financial benefits, with learning capabilities being key (Teece et al., 1997, pp. 516). Furthermore, this research also contributes to the validity of Information Processing Theory, given that it has highlighted that performance effects related to AI adoption are maximized in an uncertain information environment (Galbraith, 1973, pp. 5). By drawing together these theoretical approaches, this research makes an important academic contribution to the understanding of the relationship between AI and financial performance.

Practical Implications

From a practical perspective, the findings imply that the adoption of AI systems cannot be treated as a standalone investment in technology. Instead, managers and policymakers need to appreciate the fact that the financial payoff from AI investments is heavily contingent upon complementary investments in data-related infrastructure, governance, and human capital development. To this end, firms that desire to enhance their financial performance through the use of AI need to ensure proper alignment of technology and business strategies.

For accounting and financial reporting, the emerging prominence of AI-related capabilities creates significant concerns with regard to the recognition, measurement, and reporting of intangibles. It is possible that the relevant reporting standards need to change to better reflect the economic value of digital and analytical capabilities.

Limitations and Future Research Agenda

Despite its contribution, the current research also has some limitations. For instance, the current research is based on a review of only peer-reviewed journal articles published in the English language, which could have led to the exclusion of some relevant information from other sources. Additionally, the diversity of performance metrics and methodological approaches also makes the empirical results less comparable.

For future research, the current research has some promising avenues for addressing the limitations. For instance, there is a need for research that focuses on the longitudinal effects of AI adoption on financial performance, as such a research design will allow for the assessment of the value created over time. Additionally, there is a need for more refined metrics for measuring AI maturity and integration, as the current research is based on a simple dichotomy of AI adoption. Furthermore, the current research could have been more complete if there was a consideration of the qualitative research paradigm, as such a research design will allow for the assessment of the organizational mechanisms for the observed performance effects.

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